Adaptive Spectrum Assessment for Opportunistic Access in Cognitive Radio Networks

Bechir Hamdaoui
School of EECS, Oregon State University
E-mail: hamdaoui@eecs.oregonstate.edu

***Abstract*— Studies showed that the static nature of the traditional spectrum allocation methods, currently being used to share the radio spectrum, resulted in a plenty of unused spectrum opportunities that wireless devices can still potentially exploit. Fortunately, recent technological advances enabled software-defined radios (SDRs) that can switch from one spectrum band (SB) to another at minimum cost, thereby promoting dynamic and adaptive spectrum access and sharing. In this paper, we derive and study an adaptive spectrum assessment approach that allows devices to decide *how* to seek spectrum opportunities effectively. In the event when a decision is made in favor of discovering new opportunities, the proposed approach allows devices to determine the *optimal* number of SBs to be explored so that the device benefits from such an opportunistic spectrum access. This approach is optimal in that it strikes a balance between two conflicting needs: keeping spectrum assessment overhead low while increasing the likelihood of discovering spectrum opportunities. We study the effect of several network parameters, such as the primary traffic load, the secondary traffic load, and the collaboration level of the sensing method, on the optimal number of SBs that devices need to explore.**

***Index Terms*— Adaptive spectrum assessment, opportunistic spectrum access, software-defined radios, cognitive radio networks**

I. Introduction

The recently-witnessed success of wireless-based services and networks has resulted in an explosive demand for the electromagnetic radio spectrum. The spectrum supply, on the other hand, hasn't kept up with this fast demand. As a result, there is an expected shortage of spectrum supply, which prompted regulatory bodies, such as FCC (Federal Communications Commission), to think of new ways that will make use of the available spectrum more effectively.

In an effort to assess the current state of spectrum use, FCC has recently conducted a measurement-based study [1] of spectrum utilization in several major US cities. This study revealed that many portions of the spectrum are not in use for a significant period of time, thus implying the existence of plenty of spectrum *opportunities* that can still be exploited. As a result of this FCC's study as well as other similar studies [2], agencies at both levels, governmental and industrial, have concluded that in order to improve spectrum utilization, the available spectrum ought to be accessed and shared *adaptively* and *dynamically*.

As of today, the available radio spectrum is divided by FCC into spectrum bands (SBs), and statically assigned to users according to one of two models [3]: *licensed* or *unlicensed*. In the licensed model, SBs are licensed to users, referred to as *Primary* Users (PUs), who have exclusive use rights to their assigned SB. PUs are also protected against signal interference when using their assigned SB. The second model, on the other hand, consists of allowing other users, referred to as *Secondary* Users (SUs), to share the remaining spectrum (the unlicensed spectrum) in a non-exclusive manner. Unlike PUs, SUs have neither rights to, nor guarantees of, interference protection. It is important to mention that according to these FCC's current spectrum allotment models, no users except PUs (i.e., licensees) are allowed to access the licensed SBs even if these PUs are not using their SBs.

To resolve the spectrum shortage problem, FCC proposed to reform its current allotment policies to promote dynamic and adaptive spectrum access. Specifically, FCC promotes what is called *opportunistic* spectrum access; i.e., SUs are allowed to seek and use any licensed SB so long as they do not cause interference to PUs. Therefore, SUs who want to exploit spectrum opportunities should be capable of *detecting* and *locating* these opportunities without harming PUs in order to comply to FCC's interference-free, opportunistic spectrum access policy. For example, this detection function should enable SUs to immediately vacate the SB upon detection of PUs' presence in, or return to, their assigned SB. Spectrum detection mechanisms have been intensively studied in the literature [4–16], and can be classified into two categories: non-cooperative [4–8, 13, 15, 16] and cooperative [9–12, 14]. In the non-cooperative approach, SUs purely rely on primary transmitters' signals to determine whether a particular SB is currently being occupied by any PUs. The effectiveness of this approach in terms of SUs' ability to detect the presence of PUs depends on (1) the strength of PUs' signals and (2) the prior information that SUs have regarding PUs' signals. When PUs' signals are strong enough, SUs can measure the energy level of the received signal to decide whether a PU is present in the licensed SB [4, 5, 15]. For example, the two methods, called forward consecutive mean excision (FCME) and cell averaging (CA), proposed in [15] for detecting signals in environments where noise power is known, are based on energy level. Hence, these approaches are referred to as *energy-based signal detection*. Energy-based detection approaches are, however, susceptible to noise, and cannot discriminate among different types of signals. On the other hand, if SUs have prior knowledge regarding PUs' signal characteristics, such as type of modulation and hoping sequences, then *feature-based signal detection* approaches [6–8] can be used to detect the presence of PUs. Unlike the energy-based detection, the feature-based detection can distinguish different types of signals. Most of the proposed approaches were evaluated through analytical and simulation tools, and not until recently has it been some experimental work on spectrum sensing detection [13]. In [13], the authors experimentally identified physical difficulties in determining the detection threshold and the in-band jamming between SUs. More recently, a sensing-period adaptation mechanism has been proposed [16]. The basic idea in [16], referred to as MAC-layer sensing, is to use MAC-layer-measurable metrics to adaptively estimate spectrum-usage patterns, and apply them to adjust sensing period in a way to minimize the scanning/discorvey delay.

One major assumption needs be made in order for the non-cooperative approaches to work is that the decision regarding the availability of a given SB is entirely based on whether a primary transmitter's signal is detectable by SUs or not. That is, based on this approach, SUs can use any SB as long as no primary signals are detected on that SB. There is a subtle issue with this assumption. Recall that it is possible for primary transmitters to be located far enough from an SU (hence, they are undetectable by SUs), but their intended primary receivers are within a close proximity to SUs. In this scenario, the absence of PUs' signals false triggers SUs to use the SB, and as a result, primary receivers will be harmed by SUs' signals. This scenario, a typical hidden-terminal problem, must be prevented. In order to increase the certainty of detecting primary signals, cooperative signal detection approaches, where SUs collaborate with each others for better signal detection, can then be used. These approaches can be implemented in a centralized way [9], where all SUs report to a central unit whose task is to locate spectrum opportunities and disseminate them to SUs, or in a decentralized way [11], where SUs distributively determine spectrum availability by exchanging information among themselves. In [14], distribution detection theory has been used to allow cooperative spectrum sensing in peer-to-peer cognitive networks. The authors in [17] propose an adaptive approach for spectrum sensing that adapts its parameters according to the characteristics of the occupancy of the spectrum being scanned. This study shows an efficiency improvements over the non-adaptive approach, presented in [18].

In this paper, we analytically derive an adaptive approach that allows SUs to decide *how* to seek spectrum opportunities. Our approach relies on the spectrum detection technique that SUs implement; hence, we assume that SUs use one of the previously-developed spectrum detection techniques to detect and locate spectrum availabilities. The proposed approach allows SUs to decide whether to switch to new SBs to discover spectrum opportunities, and if a decision is made in favor of discovering, it also determines the optimal number of SBs that ought to be sensed. This approach is optimal in that it strikes a balance between the need to keep sensing overhead minimal and the desire for increasing the likelihood of discovering spectrum opportunities. Recall that the greater the number of SBs to be sensed, the higher the probability of finding idle SBs, but also the more overhead is incurred. We study the effect of the collaboration level of the sensing approach on the performance and optimality of the proposed adaptive approach.

The rest of the paper is organized as follows. In Section II, we present the spectrum allocation and sensing overhead models, and state our objective. In Section III, we derive the probability of finding spectrum opportunities in the context of spectrum-agility. We then propose and study the adaptive spectrum assessment approach in Section IV. Section V presents numerical evaluation and analysis of the proposed approach. Finally, we conclude the paper in Section VI.

II. Spectrum Agility

We assume that each PU is assigned a licensed SB, referred to as its *home* SB (HSB), to which it has exclusive access rights. We also assume that each SU is associated with one SB, also referred to as its HSB, that it can use, leave, or return to at any time, and without prior notification. Unlike PUs, SUs are not required to prevent, nor be protected against, possible interference[1] when using their HSBs. While using their HSBs, both PUs and SUs may choose to seek and use other spectrum opportunities in other SBs. For example, the 2.4 GHz frequency band can be viewed as the HSB of an IEEE 802.11 [19] wireless LAN user, whereas a TV band can be viewed as a licensed band that the IEEE 802.11 wireless LAN user can only access opportunistically. It is important to mention that PUs do not have to seek spectrum opportunities in other SBs, nor do they have to be equipped with cognitive radios in order for our approach to work; our proposed approach works independently of whether PUs are equipped with cognitive radios, and is intended to be used by SUs to access the spectrum opportunistically. We, however, envision that spectrum-agility will be adopted by PUs as well, where although they have their own assigned HSB, PUs may still want to seek spectrum opportunities in other bands (e.g., unlicensed SBs). It is also worth mentioning that while the HSB associated with a PU typically lies in the licensed band, the HSB associated with a SU does not necessarily belong to the licensed band; in fact, such a HSB is expected to be in the unlicensed band.

A. Spectrum Allocation Model

We assume that the available radio spectrum is divided into m non-overlapping SBs, and that each SB is associated with PUs who have exclusive and flexible use rights to it. PUs are also protected against interference when using their assigned SB. Let p denote the probability that a SB is being used by PUs at any time; i.e., the traffic load on the SB due to primary traffic. We term p *primary traffic load* on SBs.

We use the notion of a secondary communication group (SCG) to signify a set of SUs who want to communicate with each other—a SCG may consist of two or more SUs, and SU members may join and/or leave the group at any time. Typically, at any time, one member in a SCG transmits information while the other members belonging to the same group will receive it (this is analogous to one member talking and the others listening in a group discussion). We assume that all members of a SCG have the same HSB, and they all must be tuned to the same SB when being involved in an ongoing communication. It is important to mention that the notion of a SCG that we use in this work (and the reason for which it is introduced) does not prevent a SU from belonging to multiple SCGs at the same time; it is, however, required that once a

[1] In order to be able to share and access unlicensed SBs, SUs usually conform to certain policy and regulations, typically dictated via standards [1].

SU joins a SCG and decides to communicate with its members, naturally, it must tune to the same SB to be able to carry such a communication. There may be multiple SCGs in the network all of which simultaneously seek spectrum opportunities in all SBs. We assume that all communication sessions in the network are generated by SCGs according to a Poisson process of arrival rate λ. The duration of each session is exponentially distributed with parameter μ. Let $\eta = \frac{\lambda}{\mu}$ denote the *secondary traffic load*.

B. Discovering Spectrum Opportunities: Sensing

In order to communicate with each other, all members of each SCG must be tuned to their HSB. While communicating on their HSB, a SCG may decide to seek for spectrum opportunities in another SB. This typically happens when, for example, the members judge that the quality of their current SB is no longer acceptable. This is typically done by continuously assessing and monitoring the quality of the SB via some channel quality metric, such as SINR and/or packet success rate. That is, when the monitored quality metric drops below a threshold that can be defined *a priori*, the SCG is triggered to start seeking for spectrum opportunities.

In this work, we assume that SUs are always tuned to their HSBs. While communicating on their HSB, SUs can then seek and exploit spectrum opportunities as they discover them. When a new opportunity is discovered on another SB, SUs make simultaneous use of both their HSB and the discovered SB. As soon as PUs return to their SB, SUs must vacate the licensed SB, and continue communicating on their HSB only. In the event that the new discovered SB is not adjacent to the HSB (which is not unlikely), SUs can use selective allocation-based OFDM techniques [20, 21] to make use of disjoint SBs.

The discovery of spectrum opportunities is done through spectrum sensing. That is, SUs should, periodically (also referred to as actively) or proactively, switch to and sense certain SBs to find out whether any SBs are currently vacant. SUs are allowed to use any SB only if the SB is sensed to be vacant (not being occupied by PUs).

C. Sensing Overhead

Unfortunately, the discovery of spectrum opportunities whether done via active or proactive spectrum sensing methods cannot be performed without a cost; there is an incurred overhead associated with spectrum sensing, which is often referred to as *sensing overhead*. Recall that prior to using a SB, a SCG must ensure that the SB is not in use by any PUs. Therefore, whenever a SCG decides to explore new opportunities in the spectrum, one or more appointed members belonging to the SCG must tune themselves to the SB to be assessed, sense the band to see whether any PUs are using it, and then switch back to their HSB. Upon returning to their HSB, these appointees *collaboratively* use a voting mechanism to decide whether the sensed SB is vacant. While the appointed SUs are performing the sensing task, all other members stay tuned to their HSB. The number δ of these appointed SUs could be as small as one (only one member performs sensing) or as large as the total number of all the members of the SCG (all members perform sensing). This number δ represents then the *degree* or *level* of collaboration associated with the sensing approach. It is worth mentioning that there is always uncertainty when determining whether a SB is available via sensing; both false positive and false negative are possible as an outcome of a sensing task. However, the higher the degree of collaboration; i.e., the more members are to perform sensing, the higher the certainty of the outcome, but also the more sensing overhead is to be incurred.

Hereafter, we will refer to the case where only one member ($\delta = 1$) is appointed to perform sensing as the non-collaborative sensing approach, and to the case where all members ($\delta = k$) are appointed to perform sensing as the fully-collaborative sensing approach. The parameter k denotes the number of members in the SCG. Hence, in the fully-collaborative sensing approach, all members of a given SCG switch to and sense the SB to be assessed when spectrum opportunities are to be discovered.

We consider four types of sensing overhead:

- *Throughput Overhead (τ_t):* Whenever a SU switches to a SB for sensing purposes, it ceases to communicate[2] during that entire sensing period, thereby limiting its achievable throughput. We use τ_t to denote this throughput overhead. τ_t is a per SU, per sensed SB metric.
- *Energy Overhead (τ_p):* Sensing also requires energy; i.e., whenever a SU performs a sensing operation, it consumes a certain amount of energy, which we will denote by τ_p. τ_p is also a per SU, per sensed SB metric.
- *Dissemination Overhead (τ_d):* Whenever the appointed members of the SCG return to their HSB after performing a sensing task, they need to disseminate the sensing result among themselves as well as all the other members. There will be an overhead associated with this dissemination, which is incurred every time a sensing operation is performed. τ_d is a per SU only metric.
- *Switching Overhead (τ_s):* Every time a SCG switches to and uses a vacant SB (discovered via sensing), it incurs an overhead, called *switching overhead* and denoted by τ_s. τ_s is a per SU only metric.

It is worth mentioning that the sensing overhead depends on (1) the sensing interval; i.e., the amount of time during which appointees perform sensing, (2) the scanning period; i.e., how frequent the sensing operation occurs, and (3) the level of collaboration of the sensing approach. The total overhead $\mathcal{C}(i, k, \delta)$ incurred as a result of having δ appointed members, belonging to a given SCG with k members, switch to, and sense, i among the m SBs can be expressed as

$$\mathcal{C}(i, k, \delta) = i\tau_t k + i\tau_p\delta + \theta(k, \delta)\tau_d k + \tau_s k \qquad (1)$$

where $\theta(k, \delta)$ is a per SU design factor that represents the level of required dissemination, which, in turn, depends on the sensing approach. $\theta(k, \delta)$ can be defined and set by the system designer. Intuitively, this factor, which depends on the group size k and the degree of collaboration δ, should increase with δ for a given k. That is, the higher the number of members that perform sensing, the more dissemination overhead, but also the

[2] This work assumes that each SU can either transmit or receive, but not both, at the same time. Therefore, when a SU switches to a SB to sense it, it must cease its communication in order to be able to do so.

more the reward that the switching decision returns due to the increased certainty in finding a SB (this will be discussed in more detail in Subsection IV-B). For instance, in the case of the non-collaborative sensing approach, in which only one member performs sensing, this factor $\theta(k, \delta)$ must be as low as possible since this approach necessitates the least level of dissemination; for example, if we assume that all members are within one-hop of each others, then a simple broadcast by the appointed member suffices to disseminate the sensing information. On the other hand, as the collaboration level (i.e., δ) increases towards its fullest (i.e., k), the factor should increase as well to indicate that more dissemination is required as a result of having more members perform sensing. In this work, we choose to use $\theta(k, \delta) = \frac{\delta}{k}$, where the dissemination overhead factor increases proportionally with the level of collaboration. It is important to mention that our model is applicable regardless of the choice of the dissemination factor, and so is our adaptive spectrum assessment scheme that we develop in this paper. In fact, depending on the sensing approach, it is not unlikely that the dissemination overhead is not proportional to δ. In general, provided the sensing approach, one can first derive $\theta(k, \delta)$ and then apply Eq. (1) to compute the total sensing overhead.

Note that during the sensing operation of a SB, all the k members of the SCG will suffer from not being able to communicate during the entire sensing period. On the other hand, only the appointed members consume energy during the sensing period; i.e., there is no energy overhead associated with sensing for non-appointed SUs.

D. Objective

The objective of this paper is to develop an adaptive method that SCGs can use to decide on how to seek and exploit bandwidth opportunities across the various licensed SBs. We introduce the notion of spectrum assessment benefit via a net profit function to represent the difference between the reward and the cost resulting from the act of finding and exploiting spectrum opportunities; that is, the tradeoff between the need for increasing the chances of successful discovery of opportunities and the desire to reduce the sensing overhead associated with such an operation. Based on this net profit function, we derive an approach that allows SUs to determine the optimal number of SBs that ought to be sensed when a decision in favor of spectrum discovery is made. Recall that the more SBs to be sensed, the higher the probability of finding idle SBs, but also the more overhead to be incurred. This approach is optimal in that it strikes a balance between the need to keep sensing overhead minimal and the desire for increasing the likelihood of discovering spectrum opportunities.

III. A Probabilistic Analysis

The goal of this section is to determine the likelihood that a given SCG finds an opportunistic SB among the m available SBs. To make the math more tractable and easy to deal with, we break the problem into two steps. In the first step, we determine the likelihood that a SCG finds an available SB under the assumption that no PUs are present in the system. In the second step, we use the theory developed in the first step to solve the problem in the presence of PUs.

A SCG is required to sense a SB in order to be able to exploit it, and only if the SB is sensed vacant that the SCG can then use it for communication. In the event that all SBs are found occupied, a SCG should continue using its home channel, HSB, only.

A. Markovian Analysis Without PUs

In this section, we use Markovian analysis to compute the probability that a SB is available provided that none of the SBs are being used by PUs; only SUs compete for SBs. We model the spectrum condition as a Markovian chain with 2^m states. Each state Q, denoted by $(i_1, i_2, \ldots, i_m) \in \{0, 1\}^m$, is an m-uplet of binaries where an element $i_j \in Q$, $j \in \{1, 2, \ldots, m\}$, represents the condition of SB j. That is,

$$\text{SB } j \text{ is } \begin{cases} \text{available}, & \text{if } i_j = 0; \\ \text{occupied}, & \text{if } i_j = 1; \end{cases}$$

Let Q_i denote the set of all the $\binom{m}{i} = \frac{m!}{i!(m-i)!}$ states that have exactly i occupied SBs. Now by considering the new Markovian chain whose states are the sets Q_i, $0 \leq i \leq m$, the stationary distribution π'_i, $0 \leq i \leq m$, of being in state Q_i can be expressed as

$$\pi'_i(m) = \eta^i \frac{1-\eta}{1-\eta^{m+1}}$$

Given that all states within the same set Q_i each exists with an equal chance, the probability that i particular SBs (and only those SBs) among m SBs are each occupied by a SCG is given by

$$\pi_i(m) = \frac{\eta^i}{\binom{m}{i}} \frac{1-\eta}{1-\eta^{m+1}}$$

Hence, the probability that a particular SB i_0 (and only SB i_0) is occupied provided that exactly any $i-1$ other SBs are also occupied is

$$\bar{\pi}_i(m) = \binom{m-1}{i-1} \pi_i(m) = \frac{\eta^i (1-\eta) i}{m(1-\eta^{m+1})}$$

Using the above stationary distribution, the probability that a particular SB i_0 (and only SB i_0) among m SBs is vacant provided that no PUs are present in the system can be expressed as

$$p_0(m) = 1 - \sum_{i=1}^{m} \bar{\pi}_i(m) = \frac{\eta^{m+1} - (m+1)\eta + m}{m(1-\eta)(1-\eta^{m+1})} \qquad (2)$$

B. Markovian Analysis With PUs

Recall that the goal is to determine the likelihood that a given SCG finds an opportunistic SB among the m available SBs. The approach we propose that a given SCG adopts is as follows. The SCG starts sensing SBs one by one, and stops when it succeeds in finding an idle one. If we assume that the SCG is limited to sensing i SBs only among all the m available SBs, then the question that naturally arises is: what are the chances that the SCG finds one available SB among those i SBs. We will answer this question in this section; i.e., we will derive the probability $q_i(m)$ that a SCG finds one available SB when sensing i SBs, $1 \leq i \leq m$, among the m SBs available in the system.

We first start with the case of $i = 1$, that is, we first derive the probability that a given SB is available for a SCG in the presence of PUs.

We introduce the following events:

$A_i \equiv$ event that SB i is occupied by a PU.
$B_i \equiv$ event that SB i is occupied by a SU.
$C_i \equiv$ event that SB i is occupied by either a PU or a SU.

Note that $\Pr\{A_i\} = p$ and $\Pr\{B_i|\bar{A}_1, \bar{A}_2, \ldots, \bar{A}_m\} = 1 - p_0(m)$ for all $i \in \{1, 2, \ldots, m\}$, where $\bar{A}_i$ denotes the complement of A_i and $p_0(m)$ is given by Eq. (2) above (Pr stands for probability). By recursively using the law of total probability, the probability $q_1(m)$ that a particular SB i_0 (and only SB i_0) is vacant (not being used by any PU, nor any SU) can be written as

$$q_1(m) = 1 - p - \sum_{j=1}^{m} \binom{j-1}{m-1} p^{m-j}(1-p)^j(1 - p_0(j)) \quad (3)$$

where $p_0(j)$ is given by Eq. (2) for all $j = 1, 2, \ldots, m$.

Remark 1: The derivation of Eq. (3) is given in Appendix VI-A.

We now derive the probability $q_i(m)$ when $i \geq 2$ as a function of $q_1(j)$ for $j = 1, 2, \ldots, m$. Without loss of generality, let $1, 2, \ldots, i$ be the sensing order. By observing that $q_i(m)$ is the probability that SB 1 is available, SB 1 is not available and SB 2 is available, or SBs $1, 2, \ldots, i-1$ are not available and SB i is available, one can write

$$q_i(m) = q_1(m-i+1) + \sum_{s=0}^{i-2} q_1(m-s) \prod_{j=s+1}^{i-1} (1 - q_1(m-j)) \quad (4)$$

for $i \in \{2, 3, \ldots, m\}$, where $q_1(j)$ is given by Eq. (3) for all $j = 1, 2, \ldots, m$.

Remark 2: The derivation of Eq. (4) is given in Appendix VI-B.

IV. Optimal Spectrum Discovery

In this section, we aim to derive an adaptive approach that SUs can use to decide whether and how to seek spectrum opportunities. The basic idea is as follows. While using their HSB, SCGs may want to seek spectrum opportunities in other spectrum bands. To do so, at any time, a SCG tunes to a particular SB to assess its availability, and if the SB is found idle, the SCG can then use it along with its HSB. There are two questions that naturally arise: (1) when should a SCG seek for new spectrum opportunities? and (2) how many SBs among the m SBs should a SCG scan for discovering opportunities? Recall that the more and/or the more often SBs are scanned, the higher the chances of finding opportunities are, but also the more sensing overhead is incurred.

The objective of this section is then to derive an optimal approach that permits SUs decide when to switch to new SBs to discover spectrum opportunities, and if a decision is made in favor of discovering, it also determines the optimal number of SBs that ought to be sensed. This approach balances between the need to keep sensing overhead low and the desire to increase the likelihood of discovering spectrum opportunities. The study accounts for the collaboration level of the sensing approach via the parameter δ.

A. Switching Model and Decision

Although while using their HSBs, SCGs may decide to seek and use new spectrum opportunities at any time, in practice, such a decision may be based on a particular quality of service (QoS) metric that characterizes HSB, such as SINR, or packet success rate, that SCGs can monitor in real-time. Let $\gamma(i)$ denote the QoS level associated with SB i. It is when $\gamma(i)$ drops below *a priori* defined threshold $\bar{\gamma}(i)$ that a SCG, currently using HSB i, can seek new opportunities by switching to, and sensing, other SBs.

B. Optimal Number of SBs

We now want to answer the following question. When a SCG decides to explore new spectrum opportunities (for example, when $\gamma(i)$ drops below $\bar{\gamma}(i)$), what will the optimal number of SBs that the SCG should scan be?

Let's assume that a SCG gets a reward $\Re$ if it successfully finds an opportunistic SB. If no SB is found, then the reward is 0. Recall that there will always be a cost (overhead) associated with each attempt of discovering new spectrum opportunities, and this is regardless of whether the SCG gets a reward. This cost is explained and determined in Section II-C. There are two design options of the reward $\Re$ that one can use, each of which is applicable to a different class of applications. Option 1—A binary reward $\Re$: In this option, a SCG is assumed to either receive a full reward $\Re$ when switching to a SB, or to not receive a reward at all ($\Re = 0$). In this design option, $\Re$ is kept the same across all SBs. The idea here is that a SCG would not want to switch to a new SB unless this new SB guarantees a minimum level of QoS; e.g., minimum bandwidth. In other words, a SCG decides to switch to a new SB only when the SB's offered QoS is above a certain threshold (it then gets a full reward $\Re$), and it decides not to switch to the new SB when the SB's offered QoS is below the threshold (it then gets a 0 reward). A SB is then considered "vacant" only when its QoS level is above a certain level. This model fits well with inelastic applications, such as voice and video applications. Now the question that arises naturally is: how can the SCG assess a SB's QoS level via a detection method? Fortunately, there are several methods recently proposed that measure QoS metrics, such as packet success rate, SINR, and channel holding time (e.g., [16]). Option 2—A SB-dependent reward $\Re$: Another option is to express $\Re$ as a function of the SB's QoS metrics. In this case, $\Re$ will not be kept constant across all SBs as it will depend on the SB's characteristics and conditions. Unlike the $0-1$ design model adopted in the first option, this model is more suitable for elastic applications, where, naturally, the reward for switching to a SB is proportional to the QoS level attainable through the SB. In this paper, we adopt the first design option. The second option is left for future work as described in Section VI.

We now introduce a net profit function $\phi(i, \delta, k, m)$ to represent the tradeoff between the need for increasing the chances of finding vacant SBs (by increasing the number i of scanned SBs) and the desire to reduce the sensing overhead (by limiting the number i of scanned SBs). The profit function $\phi(i, \delta, k, m)$ can be expressed as

$$\phi(i, \delta, k, m) = \sigma(\delta) q_i(m) \Re - \mathcal{C}(i, k, \delta) \quad (5)$$

where $\sigma(\delta) = \frac{\sigma(1)\delta}{\sigma(1)\delta - \sigma(1)+1}$, $\sigma(1) \le \sigma(\delta) < 1$, is a certainty factor that depends on how collaborative the sensing approach is. Although the trend of $\sigma(\delta)$ as a function of δ depends on the sensing approach, in general, the larger the δ (i.e., the higher the level of collaboration), the more certain the vacancy of the SB; i.e., $\sigma(\delta)$ grows with δ. $\sigma(1)$, $0 < \sigma(1) < 1$, corresponds to the certainty factor of the non-collaborative approach ($\delta = 1$), and is a design parameter to be fixed *a priori*. (The terms $q_i(m)$ and $\mathcal{C}(i, k, \delta)$ are given in Eqs. (4) and (1), respectively.)

The optimal number i^* of SBs to be sensed upon a request for discovering new spectrum opportunities is the one that maximizes the net profit function; i.e.,

$$i^* = \arg \max_{i \in \{1,2,\ldots,m\}} \phi(i, \delta, k, m) \qquad (6)$$

Note that this optimal number of SBs depends on several parameters, such as the size of the SCG, sensing overheads, and the certainty factor, that can easily be monitored and/or acquired at run time. In this work, we rely on numerical methods to solve Eq. (6) to find the optimal number of SBs that maximizes the net profit function. Finding closed-form or other-form solutions to Eq. (6) is not within the scope of this work.

C. Adaptive Assessment Approach

Any SCG can adaptively use the strategy described in Section IV-A to decide when to explore new spectrum opportunities, and when it decides to do so, it can use the approach described in Section IV-B to determine the optimal number of SBs that it must scan so that its overall net profit is maximized. That is, if at any time the quality of a SCG's HSB drops below a *priori* defined threshold (i.e., $\gamma(SCG) < \bar{\gamma}(SCG)$), the SCG first computes the optimal number i^* of SBs to be explored (using Eq. (6)) and then senses exactly i^* SBs among the m SBs.

V. Evaluation

We now evaluate and study the effect of several network parameters on the optimal number of SBs that a given SCG needs to scan so that its spectrum discovery profit is maximized. We study the effect of the primary traffic load (p), the secondary traffic load (η), the collaboration level of the sensing approach (δ), and the size of the SCG (k). For each case/scenario, the equations given in Subsection IV-B are solved via Matlab to determine the optimal number of SBs. We set the total number m of SBs to 10. The reward $\Re$ for successfully finding a vacant SB is set to 200. The certainty factor $\sigma(1)$ is set to 0.8 in this study. Recall that this factor reflects the certainty of the sensing method in telling whether the SB is vacant or not, and depends on the collaborative effort and level put by the members of the SCG in order to discover new opportunities. A value of $\sigma(1)$ equaling 0.8 means that when only one member of the SCG performs the sensing task, the certainty that what the member reports regarding the vacancy of the channel is true is 80%. This level of certainty increases with the collaboration level. The sensing overhead parameters used in this section are summarized in Table I. Recall that these sensing overhead parameters are mostly system design parameters, and hence, can easily be determined once the system is known.

symbol	description	value
$\sigma(1)$	certainty factor	0.8
$\Re$	reward	200
τ_t	throughput overhead	1
τ_p	power overhead	1
τ_d	dissemination overhead	1
τ_s	switching overhead	1
m	total number of SBs	10

TABLE I
Summary of parameters

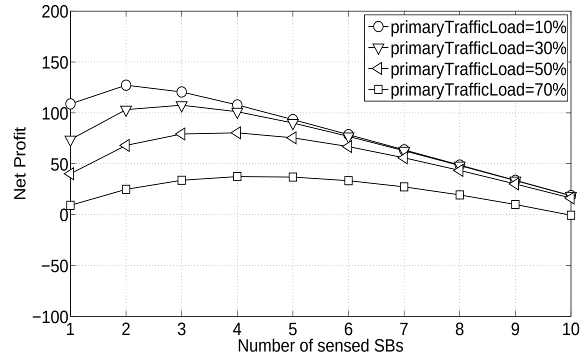

Fig. 1. Effect of primary traffic load p: $\eta = 0.6$, $k = 10$, $\delta = 5$.

A. Effect of traffic loads: primary and secondary

In Fig. 1, we show the net profit that a particular SCG receives when performing a spectrum assessment and discovery act as a function of the number of sensed SBs for different scenarios of primary traffic loads. In this study, the number of members constituting the SCG is set to $k = 10$, the level of collaboration of the sensing method is set to $\delta = 5$, and the secondary traffic load is set to $\eta = 60\%$. First, note that for each scenario, there exists an optimal number of SBs that a given SCG must scan and sense to find spectrum opportunities. While a small number of SBs incurs little sensing overhead, it also limits the chances for SCGs to discover vacant SBs. On the other hand, augmenting the number of SBs to be sensed increases the chances of finding spectrum opportunities, but not without incurring extra sensing overhead. Hence, the optimal number strikes a balance between the need for increasing the likelihood of finding a vacant SB and the desire for keeping the

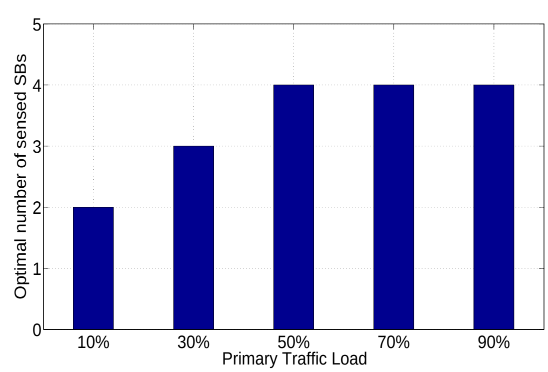

Fig. 2. Optimal number of SBs as a function of primary traffic load p: $\eta = 0.6$, $k = 10$, $\delta = 5$.

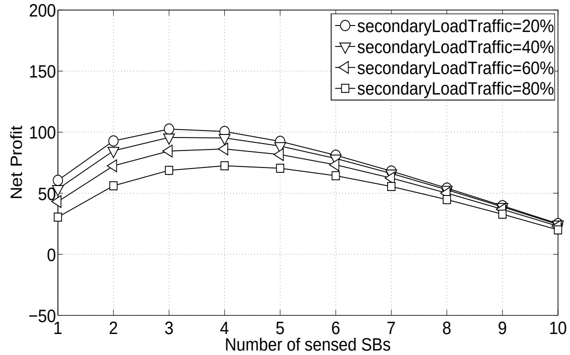

Fig. 3. Effect of secondary traffic load η: $p = 0.5$, $k = 10$, $\delta = 5$.

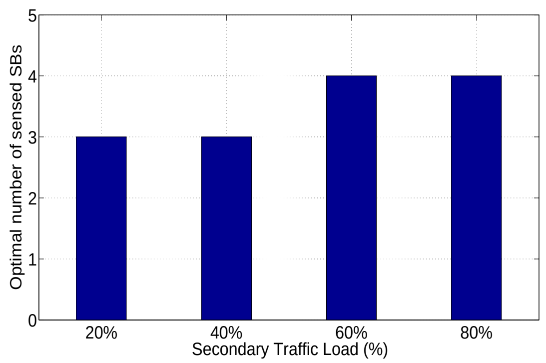

Fig. 4. Optimal number of SBs as a function of secondary traffic load η: $p = 0.5$, $k = 10$, $\delta = 5$.

sensing overhead minimum. Also observe that, as expected, the lower the primary traffic load, the the higher the net profit. In Fig. 2, we plot the optimal number of SBs for different values of primary traffic loads. Note that the higher the primary traffic load, the greater the number of SBs that a SCG ought to sense so that its profit is maximized.

In Fig. 3, we show the net profit that a particular SCG receives when trying to discover a spectrum opportunity as a function of the number of sensed SBs for different scenarios of secondary traffic loads. In this study, the number k of SCG members is set to 10, the level of collaboration is set to $\delta = 5$, and the primary traffic load is set to $p = 50\%$. Similarly, the lower the secondary traffic load, the higher the net profit. Also, we observe the same optimality behavior under the effect of secondary loads; i.e., regardless of the secondary load, there is always an optimal number of SBs that a SCG shall scan so as to maximize its profit during the spectrum discovery process. The effect of the secondary traffic load on the optimal number of SBs is depicted in Fig. 4. Like the case of the primary load traffic, this optimal number increases as the secondary load increases.

B. *Effect of SCG: collaboration and size*

Fig. 5 illustrates how the optimal number of sensed SBs by the SCG varies under the effect of the level of collaboration of the sensing approach. In this study, we vary the collaborative level from 20% to 100% (full-collaborative approach). Note that the optimal number of sensed SBs is less sensitive to the

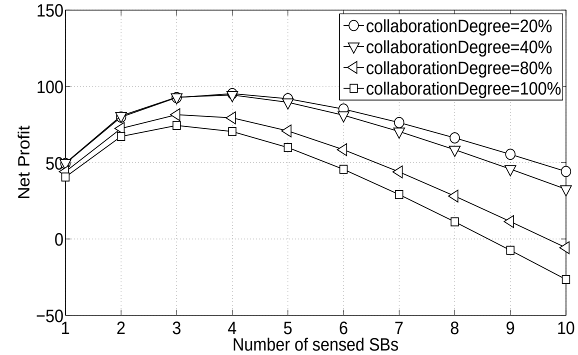

Fig. 5. Effect of the level of collaboration δ: $\eta = 0.5$, $p = 0.5$, $k = 10$.

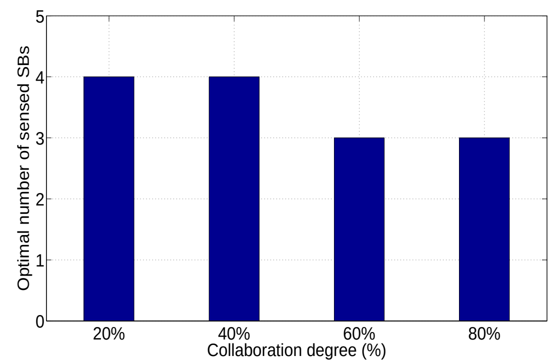

Fig. 6. Optimal number of SBs as a function of the level of collaboration δ: $\eta = 0.5$, $p = 0.5$, $k = 10$.

level of collaboration of the sensing approach than to either the secondary or the primary traffic loads. This is illustrated in Fig. 6, which plots these optimal numbers for different scenarios of collaborations. It is also worth observing that the lower the level of collaboration, the greater the optimal number of sensed SBs that maximizes the net profit. This behavior is also observed when the size of SCG is varied, as depicted in Fig. 7, in that the optimal number of sensed SBs decreases as the size k of SCGs increases. Fig. 8 shows how these optimal numbers vary when the size of SCGs change. For example, the figure shows that the optimal number of sensed SBs is 4 when the size of SCGs is 10, whereas, it is 6 when the size is 2.

In summary, this study provides a analytical method that allows each SCG, seeking opportunistic spectrum access, to determine the optimal number of SBs that it may want to scan in order to maximize its chance of finding opportunities while keeping the sensing cost minimum. It also shows how the optimal number varies under the effect of certain system parameters.

VI. Conclusion and Future Work

In this paper, we analytically derive an adaptive approach that allows SCGs to decide *whether* and *how* to seek opportunities in licensed spectra. The approach provides SCGs with the capability of (1) deciding whether to switch to new SBs to discover spectrum opportunities, and (2) determining the optimal number of SBs to be sensed if a decision is made in favor of discovering. This approach is optimal in that it

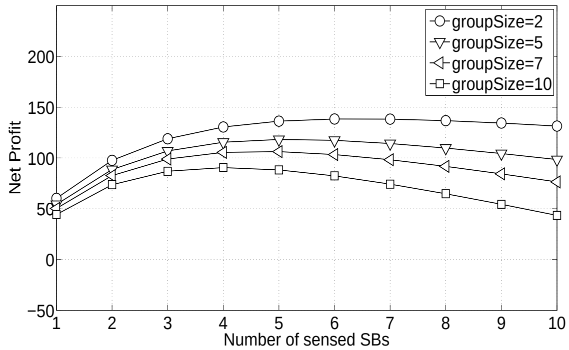

Fig. 7. Effect of SCG's sizes k: $\eta = 0.6$, $p = 0.5$, $\delta = 2$.

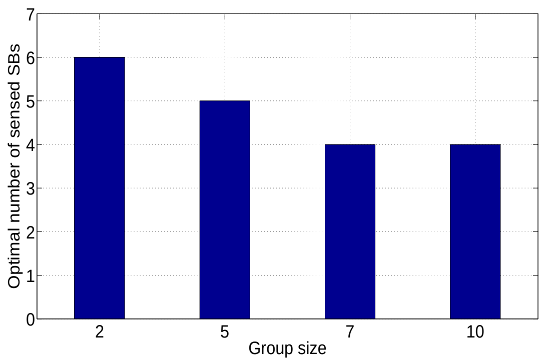

Fig. 8. Optimal number of SBs as a function of the group size k: $\eta = 0.6$, $p = 0.5$, $\delta = 2$.

strikes a balance between two conflicting needs: the need to keep sensing overhead low and that for increasing the likelihood of discovering spectrum opportunities. We study the effect of the primary traffic load, the secondary traffic load, the level of collaboration of the sensing approach, and the size of SCGs.

Recall that, in this work, we considered and studied the binary design option of the reward $\Re$, in which a SCG is assumed to either receive a full reward $\Re$ when switching to a SB, or does not receive a reward at all (i.e., $\Re = 0$), and hence, $\Re$ is the same across all SBs regardless of their conditions. This $0 - 1$ model fits well in scenarios where switching to new SB does not benefit the SCG unless it provides a certain level of QoS (e.g., bandwidth). This corresponds to the case where the applications running on the SCG are not elastic, such as voice and video applications. As mentioned in Section IV-B, another design option is consider a reward $\Re$ model in which $\Re$ depends on the SB's characteristics and quality. Unlike the studied model, this model fits well with SCGs running elastic applications, where the reward for switching to a SB is proportional to the level of QoS perceived by the SB. The study of this reward model is also of great interest as, in practice, different SBs are likely to experience different conditions and/or support different data rates. We plan to study this design option in the future. Similarly and for the same reasons, the throughput overhead τ_t model can also be chosen so that to reflect channel characteristics, such as bandwidth, modulation, channel quality, etc. As a future work, we also plan to consider and study other throughput overhead models. Another point that one can study in the future is the case when different SBs have or may have different primary traffic characteristics and loads; i.e., p is not constant across all SBs. This work considers that all SBs have the same primary traffic load p. Finally, the study of the sensitivity of the proposed approach to design parameters, such as the reward $\Re$, the factor $\sigma(1)$, the total number of SBs m, and sensing overheads, is also of a great importance, and hence, will be investigated in the future.

References

[1] *FCC, Spectrum Policy Task Force (SPTF), Report of the Spectrum Efficiency WG, November*, 2002.

[2] M. McHenry, "Reports on spectrum occupancy measurements, shared spectrum company," in *www.sharedspectrum.com/?section=nsf_summary*.

[3] *FCC, Spectrum Policy Task Force (SPTF), Report ET Docet no. 02-135, November*, 2002.

[4] A. Sahai, N. Hoven, and R. Tandra, "Some fundamental limits in cognitive radio," in *Allerton Conference on Communications, Control, and COmputing*, October 2004.

[5] F. Digham, M. Alouini, and M. Simon, "On the energy detection of unknown signals over fading channels," in *Proceedings of IEEE ICC*, May 2005, pp. 3575–3579.

[6] D. Cabric, S. Mubaraq, and R. W. Brodersen, "Implementation issues in spectrum sensing for cognitive radios," in *IEEE Conference on Signals, Systems and Computers*, Nov. 2004, pp. 772–776.

[7] A. Fehske, J.D. Gaeddert, and J. H. Reed, "A new approach to signal classification using spectral correlation and neural networks," in *Proceedings of IEEE DySPAN*, 2005, pp. 144–150.

[8] H. Tang, "Some physical layer issues of wide-band cognitive radio system," in *Proceedings of IEEE DySPAN*, 2005, pp. 151–159.

[9] G. Ganesan and Y. G. Li, "Cooperative spectrum sensing for opportunistic access in fading environments," in *Proceedings of IEEE DySPAN*, Nov. 2005, pp. 137–143.

[10] A. Ghasemi and E. S. Sousa, "Collaborative spectrum sensing for opportunistic access in fading environment," in *Proceedings of IEEE DySPAN*, 2005, pp. 131–136.

[11] J. Zhao, H. Zheng, and G.-H. Yang, "Distributed coordination in dynamic spectrum allocation networks," in *Proceedings of IEEE DySPAN*, 2005, pp. 259–268.

[12] S. Shankar, C. Cordeiro, and K. Challapali, "Specturm agile radios: Utilization and sensing architectures," in *Proceedings of IEEE DySPAN*, Nov. 2005, pp. 160–169.

[13] H. Kim, C. Carlos, C. Kiran, and K. G. Shin, "An experimental approach to spectrum sensing in cognitive radio networks with off-the-shelf IEEE 802.11 devices," in *Proceedings of IEEE Consumre Communications and Networking Conference*, 2007, pp. 1154–1158.

[14] M. Gandetto and C. Regazzoni, "Spectrum sensing: a distributed approach for cognitive terminals," *IEEE Journal on Selected Areas in Communications*, vol. 25, no. 3, pp. 546–557, April 2007.

[15] J. J. Lehtomaki, "Spectrum sensing with forward methods," in *Proceedings of IEEE MILCOM*, 2007.

[16] H. Kim and K. G. Shin, "Efficient discovery of spectrum opportunities with MAC-layer sensing in cognitive radio networks," *IEEE Transactions on Mobile Computing*, vol. 7, no. 5, pp. 533–545, May 2008.

[17] D. Datla, R. Rajbanshi, A. Wyglinski, and G. J. Minden, "Parametric adaptive spectrum sensing framework for dynamic spectrum access networks," in *Proceedings of IEEE DySPAN*, 2007.

[18] S. Jones, N. Merheb, and I.-J. Wang, "An experiment for sensing-based opportunistic spectrum access in CSMA/CA networks," in *Proceedings of IEEE DySPAN*, 2005.

[19] *IEEE 802.22, www.ieee802.org/22*.

[20] T. Keller and L. Hanzo, "Adaptive multicarrier modulation: a convenient framework for time-frequency processing in wireless communications," in *Proceedings of IEEE*, May 2000, pp. 611–640.

[21] R. Rajbanshi, Q. Chen, A. M. Wyglinski, G. J. Minden, and J. G. Evans, "Quantitative comparison of agile modulation techniques for cognitive transceivers," in *Proceedings of IEEE Workshop on Cognitive Radio Networks*, 2007, pp. 1144–1148.

Appendix

A. Derivation of Eq. (3)

Without loss of generality, let SB i_0 be SB 1. Also, let I be a subset in $\{1, 2, \ldots, m\}$ and $J = \{1, 2, \ldots, m\} - I$. By applying the law of total probability, $\Pr\{C_1\}$ can be expressed as $\Pr\{C_1|A_1\}p + \Pr\{C_1|\bar{A}_1\}(1-p)$. Since $\Pr\{C_1|A_1\} = 1$, then $\Pr\{C_1\} = p + \Pr\{C_1|\bar{A}_1\}(1-p)$. By applying the law of total probability again, we can write $\Pr\{C_1|\bar{A}_1\}$ as $\Pr\{C_1|\bar{A}_1 A_2\}p + \Pr\{C_1|\bar{A}_1\bar{A}_2\}(1-p)$, and hence, $\Pr\{C_1\}$ as $p + \Pr\{C_1|\bar{A}_1 A_2\}p(1-p) + \Pr\{C_1|\bar{A}_1\bar{A}_2\}(1-p)^2$. Now by using the law of total probability recursively, one can then write

$$\Pr\{C_1\} = p + \sum_{j=1}^{m} \binom{j-1}{m-j} p^{m-j}(1-p)^j p_c(j)$$

where $p_c(j) = \Pr\{C_1| \cap_{t\in I} \bar{A}_t, \cap_{s\in J} A_s, I \ni 1, |I| = j\}$. Observe that $p_c(j)$ represents the probability that SB 1 (and only SB 1) among a total number of j SBs is occupied given that no PUs are present. Hence, $p_c(j) = 1 - p_0(j)$, where $p_0(j)$ is given by Eq. (2) for all $j = 1, 2, \ldots, m$. Eq. (3) can now be derived by simply noting that $q_1(m)$ equals $1 - \Pr\{C_1\}$.

B. *Derivation of Eq. (4)*

We use induction to prove the result given in Eq. (4).
BASIS: $i = 2$. Note that $q_2(m)$ can be written as $q_1(m) + (1 - q_1(m))q_1(m-1)$ which also equals $q_1(m-1) + q_1(m)(1 - q_1(m-1))$.
INDUCTIVE STEP: Now by writing $q_i(m)$ as $q_{i-1}(m) + (1 - q_{i-1}(m))q_1(m-1)$ and replacing $q_{i-1}(m)$ by $q_1(m-i+2) + \sum_{s=0}^{i-3} q_1(m-s) \prod_{j=s+1}^{i-2} (1 - q_1(m-j))$, we obtain the desired result.